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Detection of Broken Bars in Induction Motors Using an Extended Kalman Filter for Rotor Resistance Sensorless Estimation

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Abstract: This paper deals with the broken bars detection in induction motors. The hypothesis on which detection is based is that the apparent rotor resistance of an induction motor will increase when a rotor bar breaks. To detect broken bars, measurements of stator voltages and currents are processed by an Extended Kalman Filter for the speed and rotor resistance simultaneous estimation. In particular, rotor resistance is estimated and compared with its nominal value to detect broken bars. In the proposed extended Kalman Filter approach, the state covariance matrix is adequacy weighted leading to a better states estimation dynamic. Its main advantage is the correct rotor resistance estimation even for an unloaded induction motor. As part of this estimation process, it is necessary to compensate for the thermal variation in the rotor resistance. Computer simulations, carried out for a 4-kW four-pole squirrel cage induction motor, provide an encouraging validation of the proposed sensorless broken bars detection technique.

Keywords: Induction motor, broken bars, rotor resistance, extended Kalman filter, simultaneous estimation.

I. INTRODUCTION

Induction motors are a critical component of many industrial processes and are frequently integrated in commercially available equipment and industrial processes. Motor driven often provide core capabilities essential to business success and to safety of equipment and personnel. There are many published techniques and many commercially available tools to monitor induction motors to insure high degree of reliability uptime. In spite of these tools, many companies are still faced with unexpected system failures and reduced motor lifetime. Environmental, duty, and installation issues may combine to accelerate motor failure far sooner than the designed motor lifetimes.

Critical induction motor applications are found in all industries and include all motor horsepowers. It has been found that many of the commercial products to monitor induction motors are not cost-effective when deployed on typical low to medium horsepower induction motors. Advances in sensors, algorithms, and architectures should provide the necessary technologies for effective incipient failure detection [1-2].

In this context, a variety of sensors could be used to collect measurements from an induction motor for the purpose of failure monitoring. These sensors might measure stator voltages and currents, air-gap and external magnetic flux densities, rotor position and speed, output torque, internal and external temperature, and case vibrations, etc. In addition, a failure monitoring system could monitor a variety of motor failures. These failures might include conductor shorts and opens, bearing failures, cooling failures, etc. It is apparent then that a failure monitoring system should be capable of extracting, in a consistent manner, the evidence of many possible failures from measurements from many physically different sensors [3-6].

The actual trends for induction motors monitoring and diagnostics is achieved without thermal and mechanical sensors [7-8]. Therefore, based on the work initiated by Cho in [9], we have proposed a failure monitoring system combining the induction motor physical model with a minimum number of sensors.

To be specific about the proposed failure monitoring system, this paper deals with the broken bars detection in induction motors. The hypothesis on which detection is based is that the apparent rotor resistance of an induction motor will increase when a rotor bar breaks. To detect broken bars, measurements of stator voltages and currents are processed by an Extended Kalman Filter (EKF) for the speed and rotor resistance simultaneous estimation. In particular, rotor resistance is estimated and compared with its nominal value to detect broken bars. In the proposed EKF approach, the state covariance matrix is adequacy weighted leading to a better states estimation dynamic. Its main advantage is the correct rotor resistance estimation even for an unloaded induction motor. As part of this estimation process, it is necessary to compensate for the thermal variation in the rotor resistance. In fact, a difficulty with broken rotor bar detection is that a variation in the rotor temperature can cause significant variation in rotor resistance. In this case, the rotor resistance, so determined, must be referred and compared to the same temperature in normal operating point.

Several approaches have been proposed, in the available literature, for rotor resistance estimation [10-12]. The purpose of using and EKF approach is to improve the rotor resistance sensorless estimation using only stator voltages and currents measurements [13]. Moreover, the advantage of using stator currents as state variable is that they are directly measurable.

II. THE INDUCTION MOTOR MODEL

Induction motors can be described by fifth order nonlinear differential equations with four electrical variables (currents and fluxes), a mechanical variable (rotor speed), and two control variables (stator voltages). In *a*-*b* axes fixed in the stator, one has

$$\Psi_0 = \begin{cases} \dot{x}_1 = -\gamma x_1 + \dfrac{K_L}{T_r} x_3 + n_p K_L x_4 x_5 + \alpha u_a \\ \dot{x}_2 = -\gamma x_2 + \dfrac{K_L}{T_r} x_4 - n_p K_L x_3 x_5 + \alpha u_b \\ \dot{x}_3 = \dfrac{L_m}{T_r} x_1 - \dfrac{1}{T_r} x_3 - n_p x_4 x_5 \\ \dot{x}_4 = \dfrac{L_m}{T_r} x_2 - \dfrac{1}{T_r} x_4 + n_p x_3 x_5 \\ \dot{x}_5 = n_p \dfrac{L_m}{J L_r}\left(x_2 x_3 - x_1 x_4\right) - \dfrac{T_L}{J} - \dfrac{f_f}{J} x_5 \end{cases}, \qquad (1)$$

where

$$\gamma = \frac{R_s}{\sigma L_s} + \frac{R_r L_m^2}{\sigma L_s L_r^2},$$

$$K_L = \frac{L_m}{\sigma L_s L_r},$$

$$\alpha = \frac{1}{\sigma L_s},$$

$$T_r = \frac{L_r}{R_r},$$

$$\sigma = 1 - \frac{L_m^2}{L_s L_r}.$$

a, b	=	stator index
u	=	stator voltage
φ	=	stator flux
i	=	stator current
R_s (R_r)	=	stator (rotor) resistance
L_s (L_r)	=	stator (rotor) inductance
L_m	=	mutual inductance
σ	=	total leakage coefficient
n_p	=	pole pair
J	=	rotor inertia
f_f	=	friction coefficient.

The stator voltages and the states are

$$\begin{cases} U^T = \left[u_a \ u_b\right] \\ X^T = \left[x_1 \ x_2 \ x_3 \ x_4 \ x_5\right] = \left[i_a \ i_b \ \varphi_a \ \varphi_b \ \omega\right] \end{cases}. \qquad (2)$$

One can consider a nonlinear system described by the following equations.

$$\dot{X} = f\left(X, U\right),$$

$$Y = H\left(X\right),$$

where $X(t)$ is a n-dimension state vector, $U(t)$ is a m-dimension control signal, and $Y(t)$ is a p-dimension measurement vector.

III. THE EXTENDED KALMAN FILTER THEORY

In this section, the extended Kalman filter theory will be briefly reviewed. The used filter is described by the following equations [13].

$$\dot{X}(t) = f\left(X(t), u(t), t\right) + G(t) w(t), \qquad (3)$$

$$Y(t) = h\left(X(t), t\right) + v(t), \qquad (4)$$

where

$G(t)$	=	state noise matrix
$w(t)$	=	state noise vector
$v(t)$	=	measurement noise vector.

The state prediction is

$$\hat{X}\left(\frac{k+1}{k}\right) = \hat{X}\left(\frac{k}{k}\right) + \int_{t_k}^{t_{k+1}} f\left(X(t), u(t), t\right) dt, \qquad (5)$$

where k is the sampling step. Using the medium value theorem, described by the following equation,

$$\int_{t_k}^{t_{k+1}} f(t) dt = \left(t_{k+1} - t_k\right) f(t) = T_s f(t), \qquad (6)$$

equation (5) can be expressed as follows.

$$\hat{X}\left(\frac{k+1}{k}\right) = \hat{X}\left(\frac{k}{k}\right) + T_s f(X) , \tag{7}$$

where T_s is the sampling period.

The filter covariance matrix is given by

$$P\left(\frac{k+1}{k}\right) = \Phi(k+1,k) P\left(\frac{k}{k}\right) \Phi(k+1,k) + Q(k) , \tag{8}$$

where the transition matrix is

$$\Phi(k+1,k) = e^{T_s F(k)} , \tag{9}$$

with

$$F = \left.\frac{\partial f}{\partial x}\right|_{x=\hat{x}} . \tag{10}$$

$\Phi(k + 1,k)$ can be linearized by the Taylor development as

$$\Phi(k+1,k) \approx 1 + T_s F(k) . \tag{11}$$

The state noise variance matrix is expressed by the following equation.

$$Q(k+1) = \int_{t_k}^{t_{k+1}} \Phi(t_{k+1}) G(\tau) Q(\tau) G^T(\tau) \Phi^T(t_{k+1},\tau) d\tau . \tag{12}$$

The Kalman filter gain is

$$K(k+1) = P\left(\frac{k+1}{k}\right) H^T(k+1) A(k+1) , \tag{13}$$

where

$$A(k+1) = \frac{1}{H(k+1)P(k+1)H^T(k+1) + R(k+1)} , \tag{14}$$

$$H(k+1) = \left.\frac{\partial h\{x(t),t\}}{\partial x}\right|_{x=\hat{x}\left(\frac{k+1}{k}\right)} , \tag{15}$$

$$h\{x(t),t\} = \left[i_a \ i_b\right]^T . \tag{16}$$

The state estimation is

$$\hat{x}\left(\frac{k+1}{k+1}\right) = \hat{x}\left(\frac{k+1}{k}\right) + K(k+1) B(k+1) , \tag{17}$$

with

$$B\left(\frac{k+1}{k+1}\right) = Y(k+1) - h\left(\frac{\hat{x}(k+1)}{k,k+1}\right) . \tag{18}$$

The updated covariance matrix filter is then given by the following equation.

$$P\left(\frac{k+1}{k+1}\right) = \left(I - K(k+1) H(k+1)\right) P\left(\frac{k+1}{k}\right) . \tag{19}$$

IV. APPLICATION TO THE INDUCTION MOTOR

The induction motor model described in section II is here used to apply the extended Kalman filter above reviewed. The state variables are selected as

$$X^T = \left[x_1 \ x_2 \ x_3 \ x_4 \ x_5 \ x_6\right] = \left[i_a \ i_b \ \varphi_a \ \varphi_b \ \omega \ R_r\right] .$$

The induction motor dynamic behavior is modeled as

$$f^T = f^T(x(t),u(t),t) = \left[f_1 \ f_2 \ f_3 \ f_4 \ f_5 \ f_6\right] ,$$

$$f = \begin{bmatrix} (-\gamma_1 - \gamma_2 x_6) x_1 + \frac{K_L}{L_r} x_3 x_6 + n_p x_4 x_5 + \frac{1}{\sigma L_s} u_a \\ (-\gamma_1 - \gamma_2 x_6) x_2 - n_p K_L x_3 x_5 + \frac{K_L}{L_r} x_6 + \frac{1}{\sigma L_s} u_b \\ \frac{L_m}{L_r} x_1 x_6 - \frac{1}{L_r} x_4 x_6 - n_p x_3 x_5 \\ \frac{L_m}{L_r} x_2 x_6 - \frac{1}{L_r} x_4 x_6 - n_p x_3 x_5 \\ n_p \frac{L_m}{J L_r} (x_2 x_3 - x_1 x_4) - \frac{T_L}{J} - \frac{f_f}{J} x_5 \\ 0 \end{bmatrix} , \tag{20}$$

where

$$\gamma_1 = \frac{R_s}{\sigma L_s} ,$$

$$\gamma_2 = \frac{L_m^2 R_r}{\sigma L_s L_r^2} .$$

The measurement matrix is given by

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} . \tag{21}$$

The Jacobean matrix, namely F, is deduced using (10).

$$F = \begin{bmatrix} -\gamma_1 - \gamma_2 x_6 & 0 & x_6 \frac{K_L}{L_r} & n_p K_L x_5 & n_p K_L x_4 & -\gamma_2 x_1 + \frac{K_L}{L_r} x_3 \\ 0 & -\gamma_1 - \gamma_2 x_6 & -n_p K_L x_5 & \frac{K_L}{L_r} x_6 & n_p K_L x_3 & -\gamma_2 x_2 + \frac{K_L}{L_r} x_4 \\ \frac{L_m}{L_r} x_6 & 0 & -\frac{x_6}{L_r} & -n_p x_5 & -n_p x_4 & \frac{L_m}{L_r} x_1 - \frac{x_3}{L_r} \\ 0 & \frac{L_m}{L_r} x_6 & n_p x_5 & -\frac{x_6}{L_r} & -n_p x_3 & \frac{L_m}{L_r} x_2 - \frac{x_4}{L_r} \\ -\frac{L_m}{JL_r} x_4 x_6 & n_p \frac{L_m}{JL_r} x_4 & n_p \frac{L_m}{JL_r} x_2 & -n_p \frac{L_m}{JL_r} x_1 & -\frac{f_f}{J} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}. \quad (22)$$

V. SIMULATION RESULTS

The proposed estimation technique has been simulated on a 4-kW squirrel cage induction motor whose ratings are summarized in the appendix.

The validity of the proposed estimation technique is well verified by simulations as illustrated by Figs. 1 and 2. It should be noticed that these results have been obtained for an unloaded induction motor, which is generally more difficult to achieve by classical methods such as those based on the active and reactive power consumption analysis [14].

To be specific about broken bars monitoring, an abrupt stepwise on rotor resistance corresponds to a broken bar condition. This situation is also well identified by the proposed EKF technique as illustrated by Fig. 1. Moreover, broken bars affect not only the rotor resistance but also the magnetic flux leading to the decrease of the output torque capability (Fig. 3).

The rotor resistance is estimated with 1 and 3%-error. Further, the spread of successive estimates given with or without broken bars is such that this increase is unambiguous, even considering manufacturing nonuniformities in the rotor. In fact, apart from the thermal compensation problem, Fig. 4 could, by itself, show that a broken bar is responsible for the increase in the rotor resistance because the proposed EKF technique provides estimates before and after bar breakage, which is not the case of the near least square error estimator proposed in [9]. The proposed estimator is quite sensitive even for no-load condition as also illustrated by Fig. 4. Moreover, the induction motor and the Kalman filter observer initial conditions are not identical but this situation does not affect the estimation process, which is not the case of the classical estimation methods particularly for unloaded induction motors [4].

One difficulty with the rotor resistance estimation and the broken bars detection is that a variation in the rotor temperature can cause a significant variation in R_r. A thermal variation in R_r can be misinterpreted as, or mask the effect of, a broken bar [9]. Therefore, as part of the EKF estimation process, the thermal variation in the rotor resistance is compensated for by using the same approach developed in [7]. In fact, it is easy to monitor the rotor temperature from its resistance estimation and then its temperature dependence, which is given by

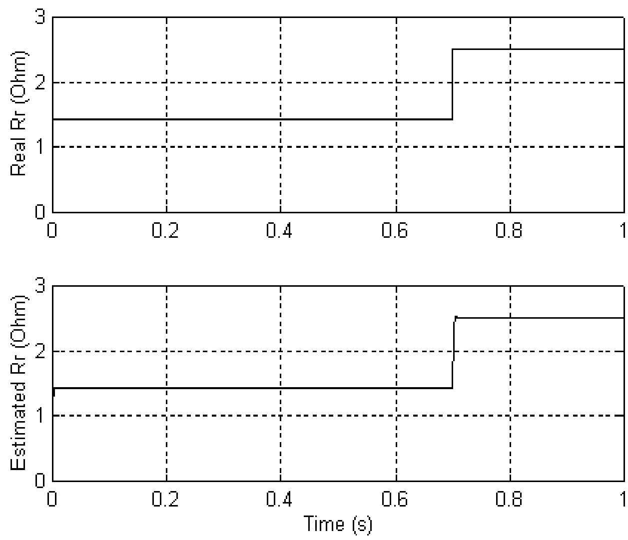

Fig. 1. Unloaded induction motor rotor resistance estimation with 74% R_r stepwise at 0.7 s.

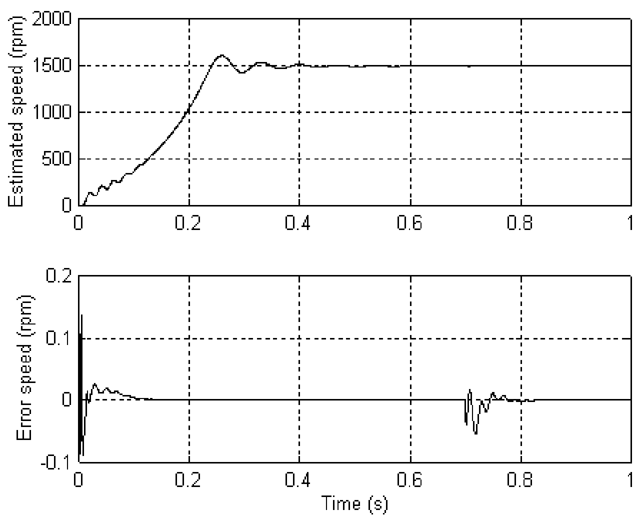

Fig. 2. Unloaded induction motor rotor speed estimation with 74% R_r stepwise at 0.7 s.

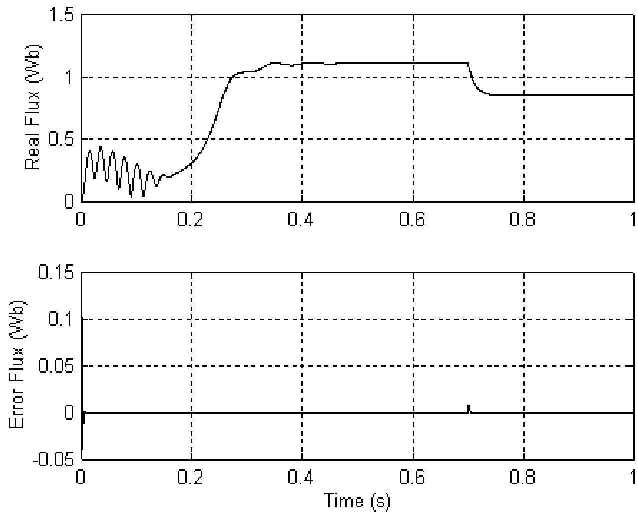

Fig. 3. Unloaded induction motor rotor flux estimation
with rotor resistance 74% stepwise at 0.7 s.

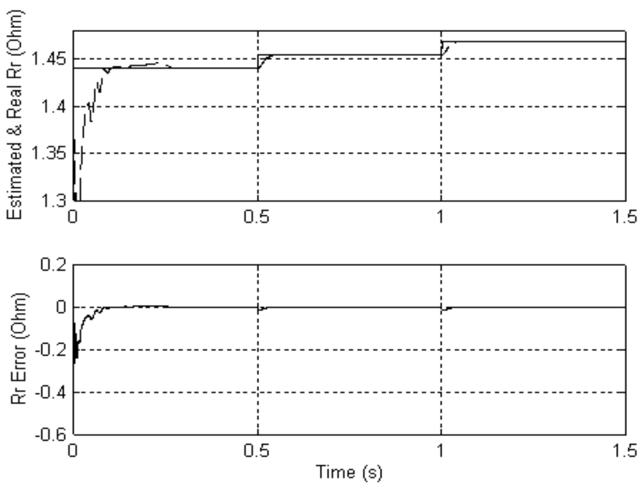

Fig. 4. Unloaded induction motor rotor flux estimation
with 1% (one broken bar) to 2% (two broken bars) rotor resistance increase.

$$R = R_0\left(1+\alpha\Delta T\right), \tag{23}$$

where

R_0	=	resistance at reference temperature T_0 = 25°C
α	=	resistance temperature coefficient
ΔT	=	temperature increase.

Equation (23) provides a means for thermally compensating R_r. Assuming that this compensation works as planned, variations in the thermally compensated rotor resistance estimation can be attributed to broken bars alone.

For illustration, the Kalman filter capability to track exponential profile, modeling the rotor resistance thermal effect, has been tested. This is shown by Fig. 5. One can notice that the estimation accuracy is quite satisfactory for monitoring purposes.

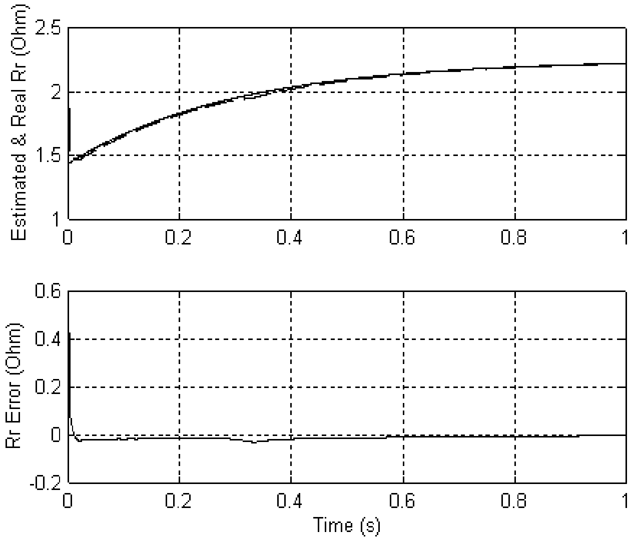

Fig. 5. Induction motor rotor resistance estimation
with a rotor resistance exponential profile variation, for a load of 10 N·m.

VI. CONCLUSION

This paper was devoted to the problem of broken bars detection in induction motors. The hypothesis on which detection is based is that the apparent rotor resistance of an induction motor will increase when a rotor bar breaks. To detect broken bars, measurements of stator voltages and currents are processed by an Extended Kalman Filter for the speed and rotor resistance simultaneous estimation. In particular, rotor resistance is estimated and compared with its nominal value to detect broken bars. In the proposed extended Kalman Filter approach, the state covariance matrix is adequacy weighted leading to a better states estimation dynamic. Its main advantage is the correct rotor resistance estimation even for an unloaded induction motor. Computer simulations, carried out for a 4-kW four-pole squirrel cage induction motor, provide an encouraging validation of the proposed broken bars monitoring technique.

APPENDIX

RATED DATA OF THE SIMULATED INDUCTION MOTOR

Rated values	Power	4	kW
	Frequency	50	Hz
	Voltage (Δ/Y)	220/380	V
	Current (Δ/Y)	15/8.6	A
	Speed	1440	rpm
	Pole pair (n_p)	2	
Rated parameters	R_s	1.150	Ω
	R_r	1.100	Ω
	l	0.013	H
	M	0.203	H
Constants	α	0.004	1/°C
	J	0.042	kg·m^2
	f_f	0.032	IS

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VIII. BIOGRAPHIES

Mohamed Saïd NAIT SAID was born in Batna, Algeria, on September 15, 1958. He received the *B.Sc.* degree in Electrical Engineering, in 1983, from the National Polytechnic Institute of Algiers, Algeria and the *M.Sc.* degree in Electrical and Computer Engineering, in 1992, from the Electrical Engineering Institute of Constantine University, Algeria. After graduation, he joined the University of Batna, Algeria, where he is a Teaching Assistant at the Electrical Engineering Institute. M.S. Naït Saïd is actually working towards a *Ph.D.* thesis on the control of induction motors in the University of Picardie “Jules Verne” at Amiens, France.

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